132270

SYSTEM AND METHOD FOR CONDITION ASSESSMENT AND END-OF-LIFE PREDICTION

RELATED APPLICATION

This application claims priority under 35 U.S.C. § 119(e)(1) to provisional application number 60/081,848 filed April 5, 1998.

BACKGROUND OF THE INVENTION

1. Technical Field

The present invention relates generally to systems and method for providing just-in-time maintenance for equipment, and more particularly, to a system and method for providing an assessment of the condition of a piece of equipment or an entire system (i.e., whether maintenance is required) and for providing a prediction for the equipment/system end-of-life.

2. Description of the Related Art

In manufacturing, power generation, oil & gas production and refining, and milling sectors, the failure of critical components results in lost revenues and emergency maintenance costs. Industry's response to this risk has been to invest heavily in scheduled preventive maintenance. The importance of detecting problems and preventing failures is reflected in the fact that as much as 15% to 40% of manufacturing production cost is allocated to maintenance. Maintenance cost is one of the highest controllable operation costs. A reliable proactive predictor of maintenance requirements of critical equipment would result in industry savings from reduced lost revenues, overtime costs associated with emergency repairs, and disrupted production schedules.

Current Just-in-Time (JIT) maintenance methods have attempted to address these issues. JIT maintenance means taking a piece of equipment off-line for servicing when it needs it, rather than according to a fixed schedule. It is expensive and time consuming to shut down critical equipment like motors, pumps, compressors and generators for maintenance, so plant operators would like to be sure that the equipment needs servicing before they schedule it. Today, maintenance schedules are based on manufacturer's specification test data. Fixed maintenance schedules result in shutting down a piece of equipment before it really needs it, or in continuing to operate one that should be overhauled. They do not take in account equipment operating history, loading profiles, and operating environments. These are some of the key factors that determine equipment life expectancy.

Current technologies typically do not measure the long-term performance and assess the health of equipment while the equipment is operating. Nor is it possible to predict equipment failures well in advance of their occurrence for adequate planning. Experience indicates that most often equipment fails when least expected and quite often immediately after a major overhaul. The life-time benefit that can be derived by a technology capable of assessing and predicting the long-term health of equipment is quite significant.

SUMMARY OF THE INVENTION

The present invention provides a system and method for condition assessment and end-of-life prediction that substantially eliminates or reduces disadvantages and problems associated with previously developed equipment maintenance systems and methods.

According to one aspect of the present invention, the condition assessment and end-of-life prediction system of the present invention includes two virtual instruments: a virtual condition assessment instrument and a virtual end-of-life prediction instrument. The virtual condition assessment instrument measures the condition of the equipment and includes a data capture subsystem for sampling a set of analog signals and converting them into digital signals, a model-based component to estimate disturbances and predict an expected response, a signal-based component to process output from the model-based component, a classification component to process output from the signal-based component, a fuzzy logic expert component to combine information from the classification component and the model-based component in order to assess the condition of the equipment, and a condition assessment panel to display the condition of the equipment. The virtual end-of-life prediction instrument predicts the equipment end-of-life and includes a condition prediction end-of-life prediction component to analyze information from the virtual condition assessment instrument to predict condition and end-of life, a prediction condition and end-of-life uncertainty estimation component to estimate the uncertainty of the condition and end-of-life prediction, and an end-of-life panel for displaying the condition and end-of-life prediction and uncertainty.

A technical advantage of the present invention is the use of software programming that uses historical data to indicate when a piece of equipment is out of calibration or in need of se~ice. This technical advantage allows the user of the equipment to minimize down time by eliminating fixed schedule off-line servicing. This eliminates

both shutting down a piece of equipment before it really needs it and continuing to operate one that should be overhauled.

Another technical advantage of the present invention is the use of software programming that uses historical data to predict the end-of-life of a piece of equipment. The present invention measures the long-term performance and assesses the health of equipment during operation. This allows a user to (I) predict equipment failures well in advance of their occurrence and (2) only replace equipment that is actually approaching end of life.

The present invention provides yet another technical advantage by providing a reliable proactive predictor of maintenance requirements of critical equipment that results in cost savings due to a reduction in equipment down time, overtime costs associated with emergency repairs, and disrupted production schedules.

BRIEF DESCRIPTION OF THE DRAWINGS

The invention itself, as well as a preferred mode of use, further objects, and advantages thereof, will best be understood by reference to the following detailed description of an illustrative embodiment when read in conjunction with the accompanying drawings, wherein:

Figure 1 shows an overview of the present invention;

Figure 2 is block diagram of an intelligent condition assessment and end-of-life prediction system;

Figure 3 shows equipment condition and end-of-life measurements inferred by physical measurements and virtual sensors;

Figure 4 depicts a model-based implementation of the ICAPS;

Figure 5 depicts a signal-based implementation of the ICAPS;

Figure 6 depicts a hybrid implementation of the ICAPS;

Figure 7 is a block diagram of a data capture and preprocessing component;

Figure 8 is a block diagram of a model-based component;

Figure 9 is a block diagram of a signal-based component;

Figure 10 is a block diagram of a classification component;

Figure 11 is a block diagram of a fuzzy logic/expert component;

Figure 12 is a block diagram of a condition assessment panel;

Figure 13 is a block diagram of a condition prediction and end-of-life prediction component;

Figure 14 is a block diagram of a predicted condition and end-of-life uncertainly estimation;

Figure 15 is a block diagram of an end-of-life panel;

Figure 16 is a block diagram of an ICAPS for coupled systems;

Figure 17 is a block diagram of a motor data capture and preprocessing component;

Figure 18 is a block diagram of a model-based component;

Figure 19 is a block diagram of a signal-based component;

Figure 20 is a block diagram of a multi-stage classification component;

Figure 21 is a block diagram of a fuzzy logic/expert component;

Figure 22 is a block diagram of a motor condition assessment panel;

Figure 23 is a block diagram of a condition prediction and end-of-life prediction component;

Figure 24 is a block diagram of a predicted condition and end-of-life uncertainly estimation subsystem;

Figure 25 is a block diagram of a motor end-of-life panel;

Figure 26 is a block diagram of an ICAPS for motor-load combinations;

Figure 27 is a block diagram of a virtual testbed for electric motor systems;

Figure 28 is a block diagram of a virtual testbed for electric generator systems;

Figure 29 graphically illustrates broken rotor bars false alarm under the prior art; and

Figure 30 graphically illustrates correct dignosis with JIT maintenance technology of the present invention.

DETAILED DESCRIPTION OF A PREFERRED EMBODIMENT

Implementations of the condition assessment and end-of-life prediction maintenance technology of the present invention are based on the following technological innovations:

- Signal processing algorithms and software programs for: (i) multi-step-ahead (including single-step-ahead) predictor (or forecasting) systems in data-rich and data-scarce environments, (ii) nonlinear disturbance estimators, (iii) nonlinear state filters, and, (iv) the uncertainty associated with the estimates in (i), (ii) and (iii);

- Intelligent Condition Assessment and End-of-Life Prediction System (ICAPS) utilizing physical (or hardware) instruments (or sensors) as inputs and inferring the system condition and system end-of-life (or remaining useful life or residual life) as outputs, including the uncertainty associated with these inferences; and

- Virtual (or software) instruments (or sensors) displaying equipment condition and equipment end-of-life information.

Figure 1 provides an overview of the present invention in broad details, and the interrelations of the various parts of the present invention are presented.

ENABLING SIGNAL PROCESSING TECHNOLOGY

Neural network software is the heart of information processing technology. Neural networks can supply reliable and critical timely information. The neural network's unique ability to learn the characteristics of man-made dynamic systems comes from the introduction of feedback into a conventional feed-forward architecture.

In general, the signal processing developments deal with estimation in non-linear systems. Algorithms that enable the construction of nonlinear predictors, in general, have been developed. These predictors are appropriate for multi-step-ahead prediction, in general, including single-step-ahead prediction in data-rich environments. The construction methods are applicable to non-adaptive and adaptive predictors. The architectures (or model structures) that the present invention can apply to include, but are not limited to, the one presented in US Pat. No. 5,479,571, which is incorporated by reference herein in its entirety. S1058 presents one embodiment of the present invention incorporated into the architecture of US Pat. No. 5,479,571, which is incorporated by reference herein in its entirety.

Additionally, algorithms that enable the construction of nonlinear state filters, in general, have been developed. Methods have been developed for the construction of non-adaptive, adaptive and hybrid state filters in data-rich environments, as described in detail later. The architectures (or model structures) that the present invention applied to includes, but is not limited to the one presented in US Pat. No. 5,479,571. S1084 presents one embodiment of the present invention incorporated into the architecture of US Pat. No. 5,479,571, which is incorporated by reference herein in its entirety.

The last component of the enabling signal processing technology consists of algorithms for the multi-step ahead prediction (or forecasting) in data-scarce environments. Because the associated uncertainty in data-scarce environments is large, a forecast uncertainty estimation algorithm has also been developed. The architectures (or model structures) that the present invention applies to includes, but is not limited to, the one presented US Pat. No. 5,479,571, which is incorporated by reference herein in its entirety. S1097 presents one embodiment of this invention incorporated into a special form of the architecture in US Pat. No. 5,479,571, which is incorporated by reference herein in its entirety.

INTELLIGENT CONDITION ASSESSMENT AND END-OF-LIFE PREDICTION SYSTEM (ICAPS)

The Intelligent Condition Assessment and End-of-Life Prediction System (ICAPS) includes a series of signal processing algorithms combined in unique ways to allow: (i) assessment of equipment condition and the associated uncertainty, and (ii) prediction of equipment end-of-life and the associated uncertainty.

Figure 2 shows a system level description of the Intelligent Condition Assessment and End-of-Life Prediction System. Figure 2 depicts the ICAPS as receiving inputs from the equipment physical sensors and the signal processing algorithms. The ICAPS can be implemented using signal processing algorithms other than the ones presented in this document. The present embodiment of ICAPS depends on the signal processing technology of S1058, S1084 and S1097, as shown in Figure 1.

A detailed description of the operation and implementation of the Intelligent Condition Assessment and End-of-Life Prediction System (ICAPS) is provided below.

VIRTUAL INSTRUMENTS FOR MEASURING EQUIPMENT CONDITION AND EQUIPMENT END-OF-LIFE

This section relates to the virtual (software) instrument (or sensors) for measuring the long-term equipment condition and equipment end-of-life aspects of the invention. There are no physical (or hardware) sensors that can measure equipment condition or end-of-life directly. Therefore, equipment condition and end-of-life measurements must be inferred by other direct (or physical) measurements and by the use of virtual sensors, as shown in Figure 3.

A detailed description of the operation and implementation of the Virtual Instruments are provided below.

I. VIRTUAL CONDITION INSTRUMENT

A virtual equipment condition instrument is defined to be a software system that is connected to a physical piece of equipment through physical (or hardware) sensors and which can accurately, continuously, non-intrusively, and in real-time or in near real-time provide equipment condition information, i.e. provide equipment condition information without the need to disrupt equipment operation and without human intervention. Here condition is broadly defined to reflect (a) the current status of incipient failures and the associated uncertainties, (b) the repairs appropriate for the current status and the costs associated with the (i) direct labor, (ii) parts, and (iii) down-time to accomplish these repairs, (c) the equipment efficiency and the costs associated with the efficiency degradation.

A detailed description of the operation and implementation of the Virtual Condition Instrument are provided below.

II. VIRTUAL END-OF-LIFE INSTRUMENT

A virtual equipment end-of-life instrument is defined to be a software system that is connected to a physical piece of equipment through physical (or hardware) sensors and which can accurately, continuously, non-intrusively, and in real-time or in near real-time provide equipment end-of-life information, i.e. provide equipment end-of-life information without the need to disrupt equipment operation and without human intervention. Here end-of-life (or remaining useful life or residual life) is broadly defined to reflect (a) expected time to failure and the associated uncertainty, (b) the predicted status of incipient failures, (c) the repairs appropriate for the predicted status and the costs that will be associated with the (i) direct labor, (ii) parts, and (iii) down-time to accomplish these predicted repairs, (d) the predicted equipment efficiency and the costs associated with the predicted efficiency degradation.

A detailed description of the operation and implementation of the Virtual

End-Of-Life Instrument are provided below.

The present invention includes the following features:

1. Signal processing
   a. Adaptive single-step-ahead prediction of measured complex system output variables, where the complex system comprises of nonlinear, stochastic and generally unknown dynamics.
   b. Nonadaptive filtering of unmeasurable (or unmeasured) complex system state variables, where the complex system comprises of nonlinear, stochastic and generally unknown dynamics.
   c. Adaptive filtering of unmeasurable (or unmeasured) complex system state variables, where the complex system comprises nonlinear, stochastic and generally unknown dynamics.
   d. Hybrid (nonadaptive and adaptive) filtering of unmeasurable (or unmeasured) complex system state variables, where the complex system comprises of nonlinear, stochastic and generally unknown dynamics.
   e. Adaptive multi-step-ahead prediction (forecasting) of measured complex system output variables, where the complex system comprises of nonlinear, stochastic and generally unknown dynamics.
   f. Uncertainty estimation (confidence interval computation) of an adaptive multi-step-ahead predictor (forecasting system) of measured complex system output variables, where the complex system comprises of nonlinear, stochastic and generally unknown dynamics.

2. System level diagnosis and prognosis
   a. Model-based diagnosis of incipient failures in complex systems, where the complex system comprises of nonlinear, stochastic and generally unknown dynamics.

b. Signal-based diagnosis of incipient failures in complex systems, where the complex system comprises of nonlinear, stochastic and generally unknown dynamics.

c. Hybrid-signal-based and model-based - diagnosis or incipient failures in complex systems, where the complex system comprises of nonlinear, stochastic and generally unknown dynamics.

d. Decoupling the effects of system inputs and disturbances on the system outputs, from the effects of system incipient faults.

e. Prognosis of incipient failures and prediction of the end-of-life of complex systems, where the complex system comprises of nonlinear, stochastic and generally unknown dynamics.

f. Estimating the uncertainty in the end-of-life of complex systems, where the complex system comprises of nonlinear, stochastic and generally unknown dynamics.

3. System specific diagnosis and prognosis

a. Model-based diagnosis of incipient failures in electric motors, electric generators of all types (electric machines, in general), electric transformers of all types, electric batteries of all types, electric motor-driven equipment of all types, i.e., pumps, fans, compressors, machine tools, valves, conveyor belts, prime movers of all types, i.e., turbomachinery, diesel engines, internal combustion engines, and process equipment, i.e., boilers, heat exchangers.

b. Hybrid-signal-based and model-based diagnosis of incipient failures in electric motors, electric generators of all types (electric machines, in general), electric transformers of all types, electric batteries of all types, electric motor-driven equipment of all types, i.e., pumps, fans, compressors, machine tools, valves, conveyor belts, prime movers of all types, i.e., turbomachinery, diesel engines, internal combustion engines, and process equipment, i.e., boilers, heat exchangers.

c. Canceling the effects of poor electric power quality from the motor stator current, electric generators of all types (electric machines, in general) electric transformers of all types, electric batteries of all types, electric motor-driven equipment of all types, i.e., pumps, fans, compressors, machine tools, valves, conveyor belts, prime movers of all types, i.e., turbomachinery, diesel engines, internal combustion engines, and process equipment, i.e., boilers, heat exchangers.

d. Canceling the effects of load torque variations from the motor stator current, electric generators of all types (electric machines, in general), electric transformers of all types, electric batteries of all types, electric motor-driven equipment of all types, i.e., pumps, fans, compressors, machine tools, valves, conveyor belts, prime movers of all types, i.e., turbomachinery, diesel engines, internal combustion engines, and process equipment, i.e., boilers, heat exchangers.

e. Prognosis of incipient failures and prediction of the end-of-life of electric motors, electric generators of all types (electric machines, in general), electric transformers of all types, electric batteries of all types, electric motor driven equipment of all types, i.e., pumps, fans, compressors, machine tools, valves, conveyor belts, prime movers of all types, i.e., turbomachinery, diesel engines, internal combustion engines, and process equipment, i.e., boilers, heat exchangers.

f. Estimating the uncertainty in the end-of-life of electric motors, electric generators of all types (electric machines, in general), electric transformers of all types, electric batteries of all types, electric motor-driven equipment of all types, i.e., pumps, fans, compressors, machine tools, valves, conveyor belts, prime movers of all types, i.e., turbomachinery, diesel engines, internal combustion engines, and process equipment, i.e., boilers, heat exchangers.

4. Virtual instrumentation

a. A virtual instrument or sensor for measuring the condition (or health) of any type of equipment in real time.

b. A virtual instrument or sensor for measuring, the end-of-life of any type of equipment in real-time.

<u>INTELLIGENT CONDITION ASSESSMENT AND END-OF-LIFE PREDICTION</u>

The Intelligent Condition Assessment and End-Of-Life Prediction System (ICAPS) architecture and its components are described in detail. The description is generic for any system with measured inputs and outputs, and it is not targeted for any specific equipment.

I. ICAPS SYSTEM LEVEL DESCRIPTION

The underlying system architecture of the Just-in-Time (JIT) maintenance technology is called the ICAPS, and it enables the implementation of the JIT maintenance technology. The ICAPS architecture performs two separate functions that are part of the functionality provided by the FIT maintenance system.

Figures 4-6 depict the "system level" architectures for three different implementations of ICAPS. Figure 4 implements a "model-based" version of the ICAPS, where the outputs of the model-based subsystem are further processed by a signal-based subsystem in order to reduce the effects of the environmental and operating conditions thus reducing false alarms and missed faults. Figure 5 depicts a purely "signal-based" implementation of the ICAPS, where the role of the model-based subsystem is assumed by the fuzzy role-based system, in addition to its role in deciding system condition. Thus the reduction of false alarms and missed faults is accomplished via a rule-based system. Figure 6 implements a "hybrid" version of the ICAPS, consisting of a model-based and a signal-based subsystems operating in parallel. The functionalities provided by ICAPS are as follows:

- System Condition Assessment (Fault Diagnosis); and
- System End-of-Life Prediction (Fault Prognosis).

Additionally, the ICAPS enables the application of the aforementioned two functions of the JIT maintenance technology, to system components that are mechanically, or other, vise, coupled, for example through a gear-box or by direct coupling.

The "system level" architecture of Figure 4 depicts the information flow from the sensor readings to the panels depicting the diagnosis and prognosis. The sensor signals are first conditioned and then sampled using a computer interface card. The sampled time-series are then processed through the "model-based" subsystem for decoupling two effects:

- The effects of the measured inputs on the measured outputs; and

- The effects of the measured (or estimated) disturbances on the measured outputs.

Additionally, the "model-based" subsystem enables the down-stream system to detect novelty, that is to classify faults not previously seen by the pre-trained classifier.

The outputs of the "model-based" subsystem are the "output residuals", that is the difference between the expected and observed system response. These residuals are then processed by the "signaled" subsystem for extraction of any spatio-temporal features. This is accomplished by first transforming the signals to the time-frequency domain via one of possible transforms, such as simple FFT, windowed- FFT, or wavelet. Then the signals are processed through a multi-stage classifier for fault classification. The outputs from the classifier and the "model-based" subsystem are processed through a filthy (rule-based) expert system which assesses the system condition and reports it to the condition panel.

Simultaneously, the condition information along with the sensed signals are processed through the end-of-life prediction system. This subsystem combines the current condition of the system with indicators, such as the ambient temperature, the electric power quality, the load cycling, and the number of start-ups to estimate the system remaining life and the uncertainty of the remaining life associated with a given confidence level. In considering the aforementioned indicators, the integral of these indicators over time must be accounted for in the end-of-life prediction subsystem because of the cumulative effect they have on the life of the equipment. These results are reported to the end-of-life prediction system panel.

The "system level" architecture of Figure 4 depicts the information flow from the sensor readings to the panels depicting the diagnosis and prognosis. The sensor signals are first conditioned and then sampled using a computer interface card. The sampled time-series are then processed through the "signal-based" subsystem. The remaining processing is similar to the case shown in Figure 4.

The "system level" architecture of Figure 6 depicts the information flow from sensor readings to the panels depicting the diagnosis and prognosis. The sensor signals are first conditioned and then sampled using a computer interface card. The sampled time-series are then processed in parallel through the "model-based" subsystem and the "signal-based" subsystem. The remaining processing is similar to the case shown in Figure 5.

II. CONDITION ASSESSMENT SUBSYSTEM

The condition assessment subsystem is composed of a number of components which work as a whole to diagnose the current condition of the equipment being assessed. The specific components that make-up the condition assessment system are now described in more detail.

A. Data Capture and Preprocessing Component

The Data Capture and Preprocessing Subsystem, as depicted in Figure 7, is the interface between the analog signals of the real world and the digital signal of the computer (virtual) world. This subsystem is implemented in hardware, for example using DAQ cards, and it converts the many signals, both system inputs and outputs, it receives into digital signals via sampling. Prior to sampling the analog signals could be conditioned using analog filtering techniques to remove high frequency components or specific low frequency. The sampling rate cab be varying, ranging up to 700 kHz or even 1 MHz.

Prior to sampling the signals are conditioned in analog form via the use of anti-aliasing low-pass filters, or other means of conditioning. Following sampling, the signals are conditioned and they are prepared for processing by the rest of the subsystems. The digital signal conditioning might take the form of additional digital filtering or scaling using some a priori known formulae. Depending on the system being diagnosed, the sampled signals could be electric voltage, electric current, rotational speed, rotational acceleration, lateral acceleration, temperature, etc.

B. Model-Based Component

The model-based component, as depicted in Figure 8, serves two broad purposes: (1) to decouple the effects of the measured (or estimated) system inputs and disturbances on the system outputs, and (2) to enable novelty detection. The component includes two subcomponents: (1) a filter to estimate any disturbances that cannot be directly measured, for example to estimate the speed or torque of the load, (2) a predictor for predicting the expected (or "healthy") response of the system under consideration. Both the filter and the predictor could be based: (1) on first-principles only, with some parameter tuning, (2) on purely empirical (or adaptively obtained) models, or (3) hybrid combination of the above two options. The filter of the model-based component can be implemented using the signal processing invention of S1084, and the predictor of the model-based component can be implemented using the signal processing inventions of S1058.

Implementations using other signal processing algorithms are also feasible.

C. Signal-Based Component

The signal-based component, as depicted in Figure 9, processes information from the model-based component outputs. This component system could also process information, in parallel, from the data capture and preprocessing component should that be necessary.

The signal-based component extracts spatio-temporal features related to faults. The expected signatures are cancelled by the model-based component, therefore the signatures (features) extracted by the signal-bases component belong to some fault class.

The signal-based component can be implemented using any of the available algorithms in the literature. The use of the signal-based component in combination with the model-based component, as done in ICAPS, gives a unique implementation.

D. Classification Component

The classification component, as depicted in Figure 10, processes information received from the signal-based component. This component is used to classify known failure modes. Having decoupled the features of "healthy" systems, the accuracy of the classification component is increased.

The classification component can be implemented using any of the available algorithms in the literature. The use of the model-based component outputs as inputs to the classification component, as done in ICAPS, gives an unique implementation.

E. Fuzzy Logic Expert Component

The fuzzy logic (rule-based) expert component, as depicted in Figure 11,

combines the information received from the classification and model-based components. This component is used to assess the system condition. Having such a component reduces the impact of false alarms and enables diagnosis of unknown failure modes.

F. Condition Assessment Panel

The condition assessment panel, as depicted in Figure 12, displays the condition information generated by the fuzzy logic rule-based expert component. This component is used to communicate: (1) the existence or lack of a fault, (2) the severity of fault, and (3) the type of a fault.

III. END-OF-LIFE PREDICTION SUBSYSTEM

The end-of-life prediction subsystem is composed of three components which work as a whole to prognosticate the expected useful life of the equipment being assessed. The specific components that make up the end-of-life prediction system are now described in more detail.

A. Condition Predation and End-Of-Life Prediction Component

The condition prediction end-of-life prediction component, depicted in Figure 13, combines the information received from the condition assessment subsystem and the data capture and preprocessing component. This component is used to prognosticate (predict) the system expected end-of-life using the currently assessed system condition and the impact of various indicators on the expected end-of-life.

B. Predicted Condition and End-Of-Life Uncertain Estimation Component

The predicted condition and end-of-life uncertainty estimation component, depicted in Figure 14, processes the information received from the condition prediction and end-of-life prediction component to obtain an estimate of the uncertainty in the expected predicted condition and end-of-life. As the actual end-of-life of the system approaches, the uncertainty computed by this subsystem decreases.

C. End-Of-Life Panel

The end-of-life prediction panel, depicted in Figure 15, displays the prognosis information generated by the end-of-life prediction and end-of-life uncertainty estimation subsystems. This subsystem is used to communicate: (1) the expected end-of-life, (2) the rate of deterioration of the expected end-of-life, and (3) the uncertainty in the expected end-of-life.

IV. CONDITION ASSESSMENT AND END-OF-LIFE PREDICTION OF MECHANICALLY COUPLED SYSTEMS

Once ICAPS is used to assess the condition and predict the end-of-life of a system, then it can be set to assess the condition and predict the end-of-life of another system to which it is coupled, using the first system as a transducer. This coupling could be mechanical or otherwise. This is depicted in Figure 16.

ICAPS IMPLEMENTATIONS

I. CONDITION ASSESSMENT SUBSYSTEM FOR MULTIPHASE AC INDUCTION MOTOR

The application of the JIT Maintenance technology presented in the previous sections to a multiphase AC induction motor is described in this section. The condition assessment system includes a number of subsystems that work as a whole to diagnose the current condition of the equipment being assessed. The specific subsystems that make-up the condition assessment system are now described in more detail.

A. Data Capture and Preprocessing Component

The Data Capture and Preprocessing Component, as depicted in Figure 17, is the interface between the analog signals of the real world and the digital signals of the computer (or virtual) world. This subsystem is implemented in hardware, for example using DAQ cards, and it converts the many analog signals, both motor inputs and outputs, it receives into digital signals via sampling. Prior to sampling the analog signals could be

conditioned using analog filtering techniques to remove high frequency components or specific low frequency components. The sampling rate can be varying ranging up to 100 kHz or even 1 MHz.

Prior to sampling the signals are conditioned in analog form via the use of anti-aliasing low-pass filters, or other means of conditioning. Following sampling, the signals are conditioned and they are prepared for processing by the rest of the subsystems. The digital signal conditioning might take the form of additional digital filtering or scaling using some a priori known formulae. The sampled signals are the three-phase voltages and three-phase currents, but they could also contain the rotational speed, the rotational acceleration, the lateral acceleration, the motor temperature, etc.

B. Model-Based Component

The model-based component, as depicted in Figure 18, serves two broad purposes: (1) to decouple the effects of the motor inputs and disturbances, that is the three-phase voltages and load torque, on the motor outputs, the three-phase currents, and (2) to enable novelty detection for faults that have not been previously encountered.

The component consists of two subcomponents: (1) a filter to estimate the motor mechanical speed or torque when it cannot be directly measured, (2) a predictor for predicting the expected (or "healthy") motor response. Both the fitter and the predictor could be based: (1) on first-principles only, with some parameter tuning, such as using the d-q-0 model, (2) on purely empirical (or adaptively obtained) models, such as using the neural networks of the JIT maintenance technology, or (3) hybrid combination of the above two options. Implementations using other signal processing algorithms are also feasible,

C. Signal-Based Component

The signal-based component, as depicted in Figure 19, processes information from the model-based component outputs, the residuals. This component could also process

information, in parallel, from the data capture and preprocessing component should that be necessary.

The signal-based component extracts spatio-temporal features related to faults. The expected signatures are canceled by the model-based subsystem, therefore the signatures (features) extracted by the signal-bases subsystem belong to some predefined fault class.

The signal-based component can be implemented using any of the available algorithms in the literature. The use of the signal-based component in combination with the model-based component, as done in ICAPS, and the use of the signal-based component in combination of the rule-based system, as done in ICAPS, gives a unique implementation.

D. Classification Component

The multi-stage classification component, as depicted in Figure 20, processes information received from the signal-based component. This component is used to classify known failure modes. Having decoupled the features of healthy systems, the accuracy of the classification component is increased.

The classification component can be implemented using any of the available algorithms in the literature. The use of the model-based component outputs as inputs to the classification component, as done in ICAPS, gives a unique implementation.

E. Fuzzy Logic Expert Component

The fuzzy logic (rule-based) expert subsystem, as depicted in Figure 21, combines the information received from the classification and model-based components. This component is used to assess the motor condition. Having such a subsystem reduces the impact of false aim-ms and enables diagnosis of unknown failure modes.

F. Condition Assessment Panel

The condition assessment panel, as depicted in Figure 22, displays the motor condition information generated by the fuzzy logic rule-based expert component. This component is used to communicate: (1) the existence or lack of a fault, (2) the severity of fault, and (3) the type of a fault.

II. END-OF-LIFE PREDICTION SUBSYSTEM FOR MULTIPHASE AC INDUCTION MOTOR

The end-of-life prediction system is composed of three subsystems which work as a whole to prognosnosficate the expected useful life of the motor being assessed. The specific subsystems that make-up the end-of-life prediction system are now described in more detail.

A. Condition Prediction and End-Of-Life Prediction Component

The condition prediction end-of-life prediction component, depicted in Figure 23, combines the information received from the condition assessment subsystem and the data capture and preprocessing component. This component is used to prognosticate (predict) the motor expected end-of-life using the currently assessed motor condition and the impact of various indicators on the expected end-of-life, such as electric power quality, motor ambient temperature, and motor load torque pulsations.

B. Predicted Condition and End-Of-Life Uncertainty Estimation Subsystem

The predicted condition and end-of-life uncertainty estimation component, as depicted in Figure 24, processes the information received from the condition prediction and end-of-life prediction component to obtain an estimate of the uncertainty in the expected motor end-of-life. As the actual end-of-life of the motor approaches, the uncertainty computed by this subsystem decreases.

C. End-Of-Life Panel

The end-of-life prediction panel, as depicted in Figure 25, displays the prognosis information generated by the end-of-life prediction and end-of-life uncertainty estimation subsystems. The subsystem is used to communicate: (1) the expected motor end-of-life, (2) the rate of deterioration of the expected motor end-of-life, and (3) the uncertainty in the expected motor end-of-life.

III. LOAD CONDITION ASSESSMENT AND END-OF-LIFE PREDICTION

Once ICAPS is used to assess the motor condition and predict the motor end-of-life, then it can be used to assess the condition and predict the end-of-life of the motor-driven equipment, such as a pump, compressor, fan, etc., using ICAPS implemented for such an equipment. The coupling could be mechanical or otherwise. This is depicted in Figure 26.

IV. VIRTUAL TESTBED FOR ELECTRIC MOTOR SYSTEMS

The above-mentioned application of the JIT maintenance technology has been tested using the virtual motor system testbed shown in Figure 27. A similar virtual generator system testbed is shown in Figure 28.

V. TECHNOLOGY DEMONSTRATION AND COMPARISON RESULTS FOR MULTIPHASE AC INDUCTION MOTOR

The JIT maintenance technology application to an AC induction motor are now presented and compared with existing technology. First, the case of healthy motor driving a pump that creates pulsations is presented. Using existing technology to diagnose this motor, one would obtain the motor current spectrum shown in Figure 29. It can be seen that the current side-bands are present indicating broken bars, when in reality the motor is in healthy condition. The same scenario is now analyzed using the JIT maintenance technology. The results are shown on Figure 30. It can be seen that the current spectrum correctly shows the existence of no motor faults.

Similar scenarios regarding rotor eccentricity and stator faults have been obtained demonstrating the effectiveness and superior performance of the JIT maintenance technology.

VIRTUAL INSTRUMENTS FOR IMPLEMENTATION OF ICAPS

The virtual instruments described in here can be used for condition assessment and end-of-life prediction in conjunction with algorithms beyond those detailed in ICAPS.

I. VIRTUAL CONDITION INSTRUMENT

A virtual equipment condition instrument is defined to be a software system that is connected to a physical piece of equipment through physical (or hardware) sensors and which can accurately, continuously, non-intrusively, and in real-time or in near real-time provide equipment condition information, i.e. provide equipment condition information without the need to disrupt equipment operation and without human intervention. If a sensor measures and displays the condition of equipment, then it must be a virtual sensor. A condition sensor is by definition a virtual (or software implemented) sensor because condition (much like quality and unlike temperature or speed or pressure) is an attribute that cannot be directly measured. A condition sensor for a piece of equipment can be constructed by using a graphical programming language, such as Visual Basic or the LabVIEW G-language. Nevertheless, a virtual sensor can also be constructed by programming it directly using a language such as C or C++.

A virtual condition sensor for a piece of equipment is a software system that displays the following (non-exhaustive) list of directly measured or inferred quantities:

1. Assessed Failure Information
   - Failure mode class that might be occurring (including the lack of failure mode, i.e. healthy operation mode) and a denied description of the failure

mode, i.e. whether a specific subfailure mode is occurring and whether there are multiple failures and how many, designated by color-coded displays;

- Severity of the failure mode, displaying the failure progression stage via color-coded information, i.e., whether Healthy, Warning or Failure;

- Urgency of the failure mode, displaying how fast the dominant failure mode(s) are developing via color-coded information, i.e. whether slow or fast using a quantifiable scale;

- If multiple failure modes are occurring simultaneously, the aforementioned failure-related information must be displayed for each assessed failure mode;

- The above-mentioned failure information can be displayed in a number of ways, including but not limited to (i) number, (ii) bar (thermometer), (iii) color-coded, (iv) graphical, (v) text, and (vi) sound;

- The aforementioned failure information can be displayed on a variety of media, such as: (i) a CRT, (ii) other monitors, (iii) a gauge, (iv) an LCD, (v) an LED.

2. Environmental and Operating Conditions - Fault Confusion Factors

- Information regarding the various environmental and operating conditions that might be instrumental in increasing the confidence level of the assessed condition. These are indicators that frequently confuse the condition assessment process.

- In the specific case of an electric motor, the quality of the power supply and the variations of the driven toad (or mechanical speed) must be displayed.

These two variables help improve the confidence in the assessed equipment condition.

3. Failure Uncertainty Information
   - For each of the failures assessed, an uncertainty level must be displayed in the form of a confidence interval.
   - The confidence interval can be bound statistically, dynamically, or model-based.

4. Efficiency and Other Performance Information
   - The efficiency of the equipment in its present condition must be computed and displayed. Any one or a combination of the methods used in operational efficiency calculations is acceptable.
   - For the computed efficiency, an uncertainty level must be displayed in the form of a confidence interval.

5. Maintenance (or Repair) Information
   - The recommended repairs for the assessed equipment condition must be displayed,
   - A priority list must be displayed for the recommended repairs, and,
   - A schedule estimate must be displayed for the recommended repairs.

6. Cost (or Savings) Information
   - The cost associated with deteriorating equipment efficiency must be displayed, on a per-unit and cumulative basis.

- The cost associated with the recommended re s must be displayed, an

- The cost associated with the down-time to perform the recommended repairs must be displayed.

7. Historical Information
   - All information 1. through 6. should be displayed in historic form, i.e., in the form of a time-series.

Furthermore, the virtual equipment condition instrument must provide sufficient real-time signal processing capabilities, such as filtering, windowing, etc., to enable a user to trade-off the various factors influencing the (accuracy) of the displayed equipment condition information in real-time.

II. VIRTUAL END-OF-LIFE INSTRUMENT

A virtual equipment end-of-life instrument is defined to be a software system that is connected to a physical piece of equipment through physical (or hardware) sensors and which can accurately, continuously, non-intrusively, and in real time or in near real time provide equipment end-of-life information, i.e., provide equipment end-of-life information without the need to disrupt equipment operation and without human intervention. If a sensor measures and displays the end-of-life of equipment, the it must be a virtual sensor. An end-of-life sensor is by definition a virtual (or software implemented) sensor because end-of-life (much like condition, quality and unlike temperature or speed or pressure) is an attribute which cannot be directly measured. An end-of-life sensor for a piece of equipment can be constructed by using a graphical programming language, like Visual Basic or the LabVIEW G-language. Nevertheless, a virtual sensor can also be constructed by programming it directly using a language such as C or C++.

A virtual end-of-life sensor for a piece of equipment is a software system that displays the following (non-exhaustive) list of directly measured or inferred quantities:

1. Predicted Failure Information - Condition Forecast

   - Failure mode class that is predicted to occur (including the lack of failure mode, i.e., healthy operation mode) and a detailed description of the anticipated failure mode, i.e. whether a specific sub-failure mode will be occurring and whether there will be multiple failures and how many, designated by color-coded displays.

   - Severity of the predicted failure mode, displaying the failure progression stage via color-coded information, i.e., whether Healthy, Warning or Failure.

   - Urgency of the predicted failure mode, displaying how fast the dominant failure mode(s) are developing via color-coded information, i.e., whether slow or fast using a quantifiable scale.

   - If multiple failure modes are predicted simultaneously, the aforementioned failure-related information must be displayed for each assessed failure mode.

   - The above-mentioned failure information can be displayed in a number of ways, including but not limited to (i) number, (ii) bar (thermometer), (iii) color-coded, (iv) graphical, (v) text, and (vi) sound.

   - The above-mentioned failure information can be displayed on a variety of media, such as: (i) a CRT, (ii) other monitors, (iii) a gauge, (iv) an LCD, (v) an LED.

2. End-of-Life Information

- The expected useful (or operational) remain~g life of the equipment ('m hours, days, weeks, months, etc.); tiffs can also be interpreted as the mean-time before failure and it can be computer in a variety of methods, such as statistically based on historical data-buses, based on current condition, etc.

- The uncertainty in the expected useful (or operational) remaining life of the equipment (in hours, days, weeks, moths, etc.).

- The confidence level in the expected useful (or operational) remaining life of the equipment (in either standard deviations or %).

3. Predicted Failure Uncertainty Information

- For each of the failures predicted, an uncertainty level must be displayed in the form of a confidence interval,

- The confidence interval can be bound statistically, dynamically, or model-based.

4. Efficiency and Other Performance Information

- The predicted efficiency of the equipment must be computed and displayed. Any one or a combination of the methods used in operational efficiency calculations is acceptable.

- For the predicted efficiency, an uncertainty level must be displayed in the form of a confidence interval.

5. Maintenance (or Repair) Information

- The recommended repairs for the predicted equipment condition must be displayed.

- A priority list must be displayed for the predicted repairs to be recommended.

- A schedule estimate must be displayed for the predicted repairs to be recommended.

5. Cost (or Savings) Information

- The cost associated with the predicted equipment efficiency must be displayed, on a per-unit and cumulative basis.

- The cost associated with the predicted repairs to be recommended must be displayed, and

- The cost associated with the down-time to perform the predicted repairs to be recommended must be displayed.

6. Historical Information

- All information from 1. through 6. should be displayed in historic form, i.e., in the form of a time-series.

Furthermore, the virtual equipment end-of-life instrument must provide sufficient real-time signal processing capabilities, such as filtering, windowing, etc., to enable a user to trade-off the various factors influencing the (accuracy) of the displayed equipment condition information in real-time.

While the invention has been particularly shown and described with reference to a preferred embodiment, it will be understood by those skilled in the art that various changes in form and detail may be made therein without departing from the spirit and scope of the invention.